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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet

Asian Network for Scientific Information

308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (16): 3576-3580, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.3576.3580

Numerical Simulation on Vehicle Characteristics of Signalized Intersection

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Abstract: Signalized intersection delay is an important evaluation index of the signalized intersection capacity and service level. This study presents a signalized intersection delay model for signalized intersection. The model uses the methods which combine the RBF neural network with stochastic service system and also uses MATLAB for computing simulation. It discusses the characteristics of the operation in the arrival and leaving process. The simulation results show that the RBF network can identify nonlinear complex systems and is more suitable for the short-term traffic forecasts. The theory of stochastic service system is practicable in vehicle delay and operating characteristic. It can provide a theoretical basis for optimizing the signal and is better to adapt the continual changes of traffic conditions than traditional methods.

Key words: RBF artificial neural network, white noise test, Jackson networks, stochastic service system

INTRODUCTION

With the rapidly economic development and increasing demands for traffic, traffic congestion impacts on people's lives more and more seriously. The transition of traffic congestion results in more operating costs and bigger accident frequency. What's more, it becomes difficult to predict the run-time. Thus some people are trying to build highly efficient roads to reduce the traffic pressure. Apart from the expansion of the road modification, people also try to improve some aspects such as traffic signals. And much knowledge of the traffic flow theory essentially involved in these researches.

Traffic flow theory (Myers and Carter, 1973; Vining and Myers, 1990) began from the 1930's, literature Lin and Tu (1995) and Kim and Lin (1998) provided some examples for the Poisson solving the problem of traffic flow by the numerical calculation. However, with the development of new transport, some original method of probability theory already does not apply to the current the traffic situation. And the new theories which have become more sophisticated, such as Queuing Theory (Mao, 1981; Zeng, 1996) and fluid Mechanics Theory, are more applicable to the present traffic conditions.

In the optimization of traffic signal system, there are many signalized intersection delay model. However, many equations for calculating delays are based on the model of Webster (Leon *et al.*, 1987). And these equations are got on the condition that has little interference and weak flow strength. Besides, they are got from the situation of foreign transport facilities and Chinese existing transport infrastructure is far from foreign situation. So the resultant conclusions may not suit to Chinese national conditions. Therefore, we need to find a new vehicle delay model based on Chinese national conditions.

In order to overcome the shortcomings of methods above, it predicts the number of vehicles that will reach the junction in the next cycle with the help of the literature Naira *et al.* (1992) which talks about the RBF artificial neural network prediction model of the arrival vehicles and tests the value with time series. It combines the forecast of vehicles with stochastic service system and use the MATLAB7.0 to calculate the delay time of vehicles in the signalized intersection and other vehicle Eigen value.

SHORT-TERM TRAFFIC FLOW FORECASTING BASED ON RBF ARTIFICIAL NEURAL NETWORK

Artificial neural network is a complex and effective way to deal with the non-linear problems which is self-organization, self-learning, adaptive, etc. It is not only widely used in areas such as pattern recognition, image processing, nonlinear system identification and adaptive control, but also widely used to predict and optimize the combination of dynamic.

At present there are many neural network topics using BP network (Hou *et al.*, 1994). The BP network's training speed and accuracy are not so good as RBF networks, as well as the right of the value of the initial impact of the results. At the same time, BP network learning process is also easy to fall into local minimum, appear a concussion and its network exists redundant connections and nodes in the learning progress.

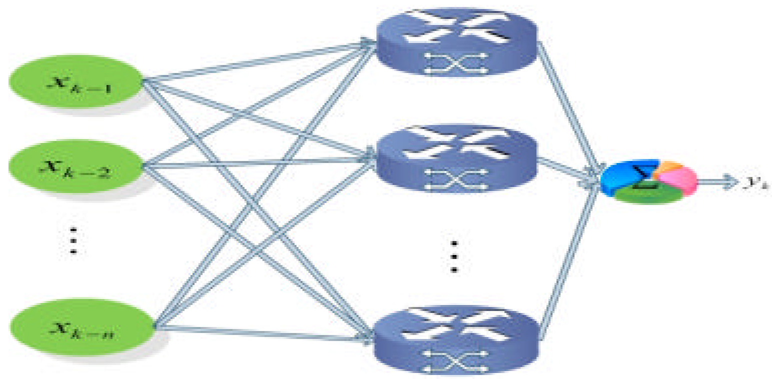

Fig. 1: RBF network prediction chart

When comes to RBF artificial neural network on its own, RBF network can identify nonlinear complex systems and are more suitable for short-term traffic forecasts. Kernel network response to the input signal generated in local which means, when the input signal nears the center of the nuclear function, hidden layer nodes will have a larger output. Therefore, this network has the capacity of local approximation.

RBF algorithm (Zhou *et al*., 1995) use k of n times before the volume of measured data traffic ($x_{k-1}, x_{k-2}, \ldots x_{k-n}$) as Network input, after the role of the middle hidden layer to form a new signal function, these new linear combination of signals constitute the network output which is the volume of traffic forecast at k time $\hat{x}_k$.

The function hidding in the role of layer nodes uses Gaussian kernel function:

$$u_j = \exp\left[\frac{(X-C_j)^T(X-C_j)}{2\sigma_j^2}\right], j=1,2,\cdots,N_h \qquad (1)$$

In the equation: u_j is the output of j hidden node, $X = (x_{k-1}, x_{k-2},..,x_{k-n})^T$ is an input sample; C_j is the center value of Gaussian kernel function; F_j is the standardization constant; N_h is for the hidden layer nodes.

RBF network's output is a linear combination of hidden layer node's output:

$$y_i = \sum_{i=1}^{N_h} w_{ij}u_j - \theta = W_i^T U \qquad (2)$$

In the equation:

$$W_i = (w_{i1}, w_{i2}, \cdots, w_{iN_h}, -\theta)^T;\ U = (u_1, u_2, \cdots, u_{N_h}, 1)^T$$

RBF network training is divided into two phases: The first phase, decide the central value C_j and F_j of Gaussian kernel function in the hidden layer node according to all the input samples; the second phase, calculate the weights of output layer W_j by using the principle of least squares. In the RBF network training, getting the hidden layer neuron number is a key issue, the past practice is to achieve alignment with the same number of input vector, obviously, when there are many input vectors, it's hard for people to accept too many hidden layer units. So that there is an improved way whose basic principle is: start training from 0 neurons, make the network increase neurons automatically by examining the output error, recycle every time and then have the input vector w1i which the greatest error corresponds to as the weight vector and create a new hidden layer neuron, then check the errors for new network. Repeat this process until it reaches the error requirements or the largest number of hidden layer neurons. It can be seen that radial basis function networks with the characteristics, such as the adaptive structure, repeating this process to determine the error until it reaches the requirements and output value has nothing to do with the initial weights. After receiving the forecast, we need to use the statistical knowledge to test the white noise. The principle can be found references, no longer describe in detail here.

TRAFFIC SIGNAL MODEL

Road networks are complex. A road network is composed by a number of signalized intersections and sections which connect these signalized intersections. Assume that the composition of the network approach as follows.

Figure 2 shows the lane distribution in each signal intersection: The map does not indicate there are how many lanes from left to right. It is all decided by the actual situation of every signal intersection.

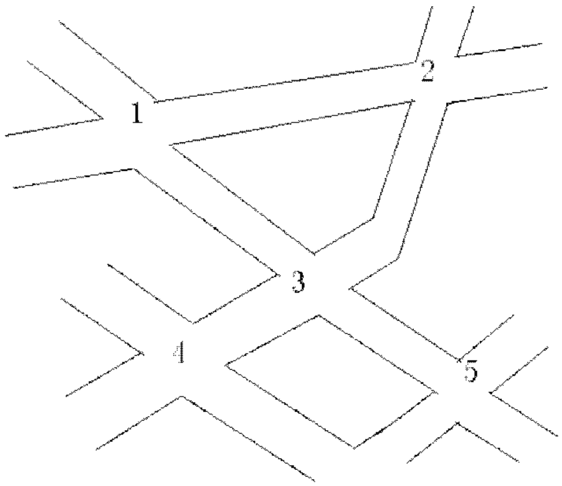

Fig. 2: Signalized intersection plane model

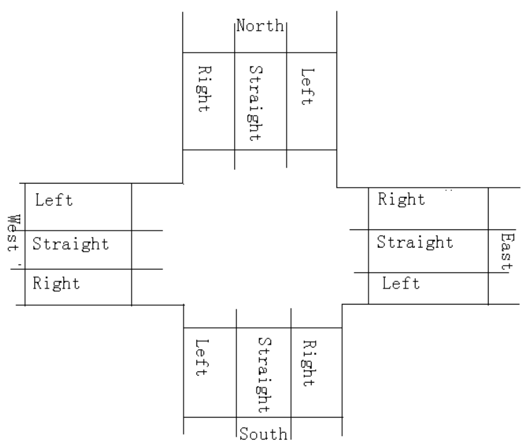

Fig. 3: Lane distribution model

The arrival rate, length of the queue and the delay time of vehicles in the traffic signal intersection are very important to the implementation of traffic signal's control and manage. In this study, stochastic service system theory is used to forecast the vehicle's arrival rate, the length of the queue and time delay in a signalized intersection.

The signalized intersection i will be saw as a service desk, all vehicles that arrived at signalized intersection i are considered as the arrival of customers (all vehicles that reach to each stop lines of signalized intersection i obey the Poisson distribution, every signalized intersection has four stop lines present different directions: East, South, West and North. and several Poisson streams' convergence still obeys Poisson distribution. So the vehicles which reach the stop line of signalized intersection i are still obey Poisson distribution). Although the signalized intersection i is controlled by signal Lights, different traffic flows can cross the intersections in different phase. But there will always be a green light in a certain phase during a complete cycle, it means that the intersection provide a continuous service for the customers vehicles. The service time from the service desk to vehicles obey the independent negative exponential distribution, thus signalized intersection i can be seen as a M/M/1 system. Total average arrival rate is shown as follows: Assuming 8_i is the arrival rate of the first vehicles from the outside to the intersection i, P_{ij} is the diversion coefficient in the signalized intersection i[13], it is the probability of the vehicle that get away from the signal intersection i and to the signal intersection j. If it is impossible to go to the signal intersection j from the signalized intersection i directly, then $P_{ij} = 0$ and:

$$\sum_{j \neq i}^{n} P_{ij} = 1 \ (0 \le P_{ij} \le 1, (i, j = 1, 2, \cdots n))$$

according the Markov process we can get the value presents the probability of each four traffic flows turn to different directions in the cycles n at signalized intersection.

Assuming Λ_i is the total average arrival rate in signalized intersection i, then according Jackson theory, we can see:

$$\Lambda_i = \lambda_i + \sum_{j \neq i}^{n} p_{ij} \Lambda_j, (j = 1, 2, \cdots n.)$$

That is:

$$\begin{cases} \Lambda_1 = \lambda_1 + P_{21}\Lambda_2 + P_{31}\Lambda_3 + \cdots + P_{n1}\Lambda_n \\ \Lambda_2 = P_{12}\Lambda_1 + \lambda_2 + P_{32}\Lambda_3 + \cdots + P_{n2}\Lambda_n \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \Lambda_n = P_{n1}\Lambda_1 + P_{2n}\Lambda_2 + P_{3n}\Lambda_3 + \cdots + \lambda_n \end{cases} \quad (3)$$

The service capacity of signalized intersection i is mostly determined by the intersection's geometric characteristics which can be seen as known. Assume the average service rate is μ_i, according to the M/M/1 system, we can predict the running characteristics and other relevant indicators of vehicles in signalized intersection i. Assume there is only one service desk and service is provided according the rule: First come, first-served. Arrival stream of customers obey Poisson distribution whose parameter is 8. Service time V obey the negative exponential distribution whose parameter is U. So the system mentioned above is called M/M/1 queuing system and in this system, customers receive services.

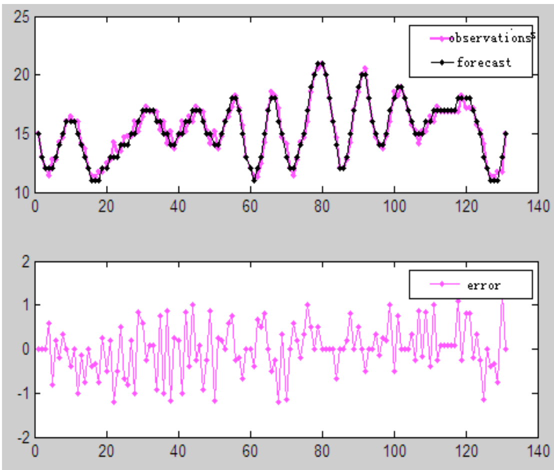

Fig. 4: Eesults of RBF neural network forecast map

Average waiting time :

$$\bar{W} = \frac{\rho}{u(1-\rho)} \tag{4}$$

The average length of stay:

$$\bar{T} = \frac{\rho}{\mu(1-\rho)} + \frac{1}{\mu} \tag{5}$$

Average length of the ranks:

$$\bar{N}_1 = \frac{\rho}{1-\rho} \tag{6}$$

And:

$$\rho = \frac{\lambda}{U}$$

is the service's intensity.

SIMULATION EXPERIMENTS

Set a busy road in Hangzhou as an example, we show arrival rate of the next signalized intersection, queue length and delay prediction in different cycles.

By the fitting toolbox of Matlab, use cubic spline interpolation method to draw 131 points of samples and also use RBF to predict a short-term traffic flow.

After SPSS testing: According to the correlation coefficient test p value in the 5 cycles before test bigger than 0.05, we can get the conclusion that this error is a white noise sequence.

Table 1: Analysis of short-term forecasts of traffic flow table

Cycle	Cubic spline (T)	Rounded (T)	RBF predictive value (a)	Rounded (a)	Error
1	10.00	10.00	10.00	10.00	0.00
2	9.83	10.00	10.00	10.00	0.00
3	9.91	10.00	10.16	10.00	0.16
4	10.17	10.00	10.16	10.00	0.16
5	10.56	11.00	10.16	10.00	-0.84
⋮	⋮	⋮	⋮	⋮	⋮
126	10.00	10.00	10.00	10.00	0.00
127	10.34	10.00	10.16	10.00	0.16
128	10.66	11.00	10.16	10.00	-0.84
129	10.92	11.00	11.25	11.00	0.25
130	11.05	11.00	10.97	11.00	-0.03
131	11.00	11.00	10.97	11.00	-0.03

Table 2 Error of the white noise testing

Autocorrelations

Series: VAR00001

Lag	Autocorrelation	Std. Errora	Box-Ljung Statistic Value	df	Sig.b
1	-0.113	0.086	1.719	1	0.190
2	0.150	0.086	4.750	2	0.093
3	0.140	0.086	7.402	3	0.060
4	-0.119	0.085	9.351	4	0.053
5	-0.018	0.085	9.395	5	0.094

Table 3: Average length of the ranks

Average leader Cycle	1	2	3	4	5
Captain	0.710555	0.565737	5.601713	0.484475	0.447034

Table 4: Average length of stay

Simulation results of The average length of stay (s)

Cycle signal	1	2	3	4	5
1	4.31	4.47	8.12	4.64	4.77
2	4.35	4.39	8.18	4.74	4.88
3	4.39	4.35	8.18	4.69	4.88
4	4.39	4.35	8.18	4.74	4.82
5	4.28	4.35	8.18	4.69	4.93
⋮	⋮	⋮	⋮	⋮	⋮
127	4.39	4.39	8.18	4.64	4.93
128	4.35	4.35	8.25	4.64	5.05
129	4.31	4.31	8.05	4.54	4.93
130	4.28	4.31	8.08	4.59	4.99
131	4.14	4.31	7.92	4.45	4.99

Table 5: Average waiting time

Simulation results of The average waiting time (s)

1	2	3	4	5
1.791315	1.616392	6.887353	1.513985	1.473739
1.806496	1.586179	6.944273	1.546198	1.506857
1.821936	1.571492	6.944273	1.529922	1.506857
1.821936	1.571492	6.944273	1.546198	1.490114
1.776387	1.571492	6.944273	1.529922	1.52398
⋮	⋮	⋮	⋮	⋮
1.821936	1.586179	6.944273	1.513985	1.52398
1.806496	1.571492	7.002142	1.513985	1.559421
1.791315	1.557074	6.831358	1.483088	1.52398
1.776387	1.557074	6.859241	1.498377	1.541497
1.719085	1.557074	6.722056	1.453426	1.541497

Then we use the theory of stochastic service system to simulate the vehicle characteristics.

The above simulation experiments show that RBF network can identify nonlinear complex systems and more suitable for short-term traffic forecasts. Through statistical knowledge, use the SPSS software to evaluate whether it is reasonable to predict the sequence, whether the residuals white noise sequence. The stochastic service system theory and operation of the delay in determining the characteristics of the vehicle is feasible proximate reality.

CONCLUSION

This study studies the characteristics of vehicles arrival and passing through the signalized Intersections. Then on the basis of it, the research use the stochastic service system theory and RBF artificial neural network to establish delay model and forecast model of vehicles in signalized Intersections. This research gives a solid theoretical foundation of enhancing the efficiency of road, reducing vehicle delay and is adapt to the rapid development of transport. And it also provides an effective method to enhance the capacity of public services.

ACKNOWLEDGMENT

This study was partly supported by the ZUCC Research Foundation with Grant No. J09002.

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